```
import pandas as pd
import matplotlib.pyplot as plt
customers=pd.read_csv("Customers.csv")
products=pd.read_csv("Products.csv")
transactions = pd.read csv("Transactions.csv")
transactions ['TransactionDate'] = pd.to_datetime(transactions['TransactionDate'], errors='coerce')
{\tt merged\_data = transactions.merge(customers, on='CustomerID', how='left').merge(products, on='ProductID', how='left')}
merged_data['TransactionMonth'] = merged_data['TransactionDate'].dt.to_period('M')
# Aggregating data for each customer
customer_features = merged_data.groupby('CustomerID').agg({
    'TotalValue': 'sum',
    'Quantity': 'sum',
    'Category': lambda x: x.mode()[0], # Most frequent category
    'Region': 'first'}).reset_index()
# Encode categorical data (Region, Category)
customer_features = pd.get_dummies(customer_features, columns=['Region', 'Category'], drop_first=True)
# Normalize numerical features
from \ sklearn.preprocessing \ import \ MinMaxScaler
scaler = MinMaxScaler()
numerical_cols = ['TotalValue', 'Quantity']
customer_features[numerical_cols] = scaler.fit_transform(customer_features[numerical_cols])
print(customer_features.head())
\overline{2}
      CustomerID TotalValue Quantity Region_Europe Region_North America
            C0001
                    0.308942 0.354839
                                                 False
                                                                        False
                     0.168095 0.290323
            C0003
                     0.249541 0.419355
     3
            C0004
                     0.497806 0.709677
                                                 False
                                                                        False
     4
            C0005
                     0.184287 0.193548
                                                 False
                                                                        False
        Region_South America Category_Clothing Category_Electronics \
     a
                        True
                                          False
                                                                  True
     1
                       False
                                           True
                                                                 False
     2
                        True
                                          False
                                                                 False
                        True
     3
                                          False
                                                                 False
     4
                       False
                                          False
                                                                  True
        Category_Home Decor
     0
     1
                      False
     2
                       True
                      False
     3
     4
                      False
from sklearn.metrics.pairwise import cosine_similarity
# Calculate similarity matrix
similarity_matrix = cosine_similarity(customer_features.drop(columns=['CustomerID']))
similarity_df = pd.DataFrame(similarity_matrix, index=customer_features['CustomerID'], columns=customer_features['CustomerID'])
# Find top 3 similar customers for first 20 customers
lookalike results = {}
for customer_id in customer_features['CustomerID'][:20]:
    similar_customers = similarity_df[customer_id].nlargest(4).iloc[1:4] # Exclude self
    lookalike_results[customer_id] = similar_customers
print(lookalike_results)
    {'C0001': CustomerID
     C0184
              0.999772
     C0048
              0.999533
     C0190
              0.998816
     Name: C0001, dtype: float64, 'C0002': CustomerID
     C0088
              0.999712
     C0092
              0.995012
     C0106
              0.992668
     Name: C0002, dtype: float64, 'C0003': CustomerID
     C0076
              0.997758
     C0052
              0.996351
     C0031
              0.995500
     Name: C0003, dtype: float64, 'C0004': CustomerID
     C0169
              0.997158
     C0087
              0.996124
     C0165
              0.991425
     Name: C0004, dtype: float64, 'C0005': CustomerID
     C0186
              0.999698
     C0146
              0.998471
     C0007
              0.998434
     Name: C0005, dtype: float64, 'C0006': CustomerID
```

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C0126
        0.999394
C0187
        0.999085
C0011
        0.998734
Name: C0006, dtype: float64, 'C0007': CustomerID
C0146
        1.000000
        0.998840
C0115
C0005
        0.998434
Name: C0007, dtype: float64, 'C0008': CustomerID
        0.990542
C0160
C0059
        0.988556
C0079
        0.987508
Name: C0008, dtype: float64, 'C0009': CustomerID
C0198
        0.999997
C0061
        0.994413
C0062
        0.992539
Name: C0009, dtype: float64, 'C0010': CustomerID
        0.996443
C0111
C0062
        0.996210
C0103
        0.992799
Name: C0010, dtype: float64, 'C0011': CustomerID
        0.998734
C0006
        0.998146
C0137
C0126
        0.997875
Name: C0011, dtype: float64, 'C0012': CustomerID
C0163
        0.999544
C0113
        0.998042
C0195
        0.997173
Name: C0012, dtype: float64, 'C0013': CustomerID
        0.998081
C0099
C0108
        0.997441
        0.984848
C0107
Name: C0013, dtype: float64, 'C0014': CustomerID
C0060
        0.999876
C0089
        0.982982
C0172
        0.976630
Name: C0014, dtype: float64, 'C0015': CustomerID
C0131
        0.993145
```